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Integrated Data Hiding and Compression Scheme Based on SMVQ and FoE Inpainting

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Abstract

Data Hiding and Compression are equivalently significant terms in the field of communication and its study is inevitable. In this paper, a novel joint data hiding and compression system is ventured based on VQ, SMVQ and image inpainting. Data hiding and compression scheme are melded into a single unit which will increase the efficiency of communication. As a pre-processing step, the image is divided into non overlapping blocks. The topmost and leftmost blocks are compressed by employing VQ and the residual blocks are embedded with secret data and compressed simultaneously by SMVQ or image inpainting adaptively according to the secret bit to be hidden. VQ is also employed on a threshold basis for some blocks to control the distortion. The concatenated codes received are segmented into indices and secret bits according to the indicator bits. On the receiver side, FoE based inpainting was used for reconstructing lost parts of image. Experimental results validates satisfactory performance in terms of compression ratio and image quality.

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Keywords: Data hiding; image compression; vector quantization (VQ); side match vector quantization (SMVQ); image inpainting; FoE

1. Introduction

Nowadays, the development and appetite for multimedia product grows increasingly fast, contributing to insufficient bandwidth of network and storage memory device. The image compression schemes are aimed to reduce

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the transmission rates for still images without sacrificing much of the image quality. Although many compression standards have been developed and are available, there is a need to design more efficient coding algorithms.

Another important issue is the transmission of private data securely. Protecting important data from being accessed illegally by unauthorized users become more and more significant. Cryptographic techniques, such as DES and RSA, are not suitable for encrypting the important data directly, since the ciphered results are always distorted and meaningless, which readily attracts the attention of malicious attackers. As a remedy to this limitation, a prevalent technique called steganography has been developed. The primary concept of steganography is to embed the important data into a cover image to create a stego image such that the attackers cannot perceive the existence of important data. That is hidden data is camouflaged in a stego image and cannot be detected easily by unauthorized users.

In recent times, many data hiding schemes for the compressed codes have been reported which can be applied to diverse compression techniques. Among them, vector quantization (VQ) based data hiding methods are attractive especially because the VQ [3]-[6], [8] technique is a block based quantization method with the benefits including simple architecture, efficient decoding procedure, and easy implementation. In the VQ process, each block is represented by an index and only the indices are transmitted achieving compression. At the receiver side, the table look up decoding is undertaken and each index is replaced by the corresponding codeword.

Du and Hsu(2003)[4] proposed an adaptive data hiding method for VQ compressed images, in which embedding process can be revised according to the amount of hidden data. The VQ codebook was subdivided into two or more sub codebooks, and the best match in one of the sub codebooks would hide the secret data. VQ compression rate could be further increased by search order coding scheme proposed by Hseih and Tsai[9] and achieve better performance of the bit rate through searching nearby identical image blocks following a spiral path.

Chin et al. (2007) [14] proposed a reversible data embedding technique which was based on vector quantization and realized the recovery of original VQ index table after extraction. The scheme used codebook which had been clustered to groups for secret embedding and data recovery. A preprocessing stage was employed to enhance data embedding capacity where the code words were reordered according to their referred counts and the concepts of frequency clustering and trio extension was incorporated. Chin Chen Chang, The Duc Kieu and Yung Chen Chou (2009) successfully applied the LAS algorithm [3] to compressing VQ index tables and developed a new approach to embedded secret data into VQ index tables. However, the method reads through a VQ index table from left to right and from top to down. Their scanning strategy does not sufficiently apply the locality of index tables. In order to improve this shortcoming, a fractal Hilbert- curve strategy [6] was proposed by Chen Hsing Yang and Yi-Cheng Lin (2010). The walking trace of fractal Hilbert curve causes that some indexes will frequently appear within a part of the trace, which is suitable for the LAS method. Following the fractal curve to process the VQ index table results in better compression rates in the data embedding procedure.

Side Match Vector Quantization[10]-[12] was proposed as an improved version of VQ to achieve higher compression and to alleviate the block artifact in which both the codebook and the sub codebooks are used to generate the index values for the residual blocks. Many researches have been done on embedding secret message by SMVQ. In 2006, Chin et al. presented a reversible data hiding scheme based on SMVQ [15] where the preprocessed data was embedded in the SMVQ compressed image. If the secret bit is 1, the corresponding codeword of sub codebook was modified with an approximate codeword and the codeword was unaltered otherwise. The restoration of the original SMVQ index values and secret extraction can be achieved at the receiver side. Chang Chu Chen and Chin Chen Chang proposed a high capacity image-hiding scheme based on an adaptive index in 2010[20]. It was proposed to overcome the drawback of SMVQ hiding capacity being low as only one bit is hidden in one index code. The weighted squared Euclidean distance (WSED) can also be used to increase the probability of SMVQ to get greater hiding capacity.

Chin et al.(2014)[2] proposed a novel lossless image compression scheme that combines side match vector quantization and the Huffman Coding algorithms to further improve the compression rates. The technique first transforms an image using the SMVQ technique to generate a transformed index table which is encoded with the Huffman encoding algorithm.

In all the schemes mentioned in the paper, data hiding is always conducted following image compression, i.e. both work as separate modules on the sender side. The motive is to conglomerate the functions of data hiding and image compression which can avoid the risk from suspicious attackers with considerable image quality and high compression ratios and compare the performance of the proposed scheme with median diffusion inpainting.

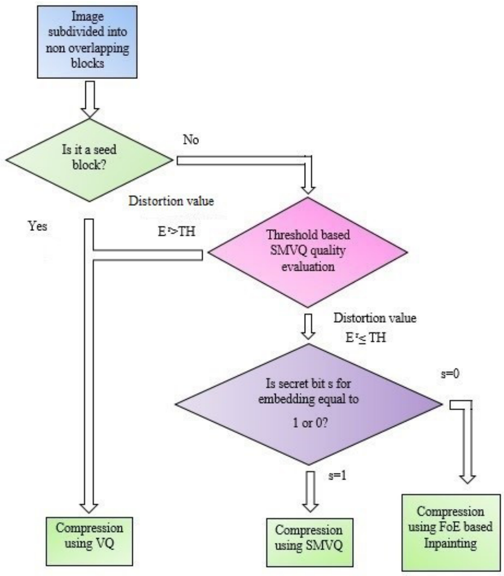


Figure 1.Flowchart of compression and secret data embedding for each block

2. Integrated Data Hiding and Compression Scheme

In the proposed scheme rather than two individual modules, a single module is used to actualize the two functions of data hiding and image compression simultaneously. According to the secret bits, the compression techniques of SMVQ and image inpainting is adaptively chosen. After receiving the compressed codes, one can extract the secret bits successfully during the image decompression.

A similar work was done by Chuan et al. [1] where the PDE based inpainting technique was used for compression. Details in the unknown region was created through propagating the available information along isophote directions. The variation of smoothness is estimated using Laplacian and is projected onto the direction of isophote. It is assumed that the projection value is equal to the change of image gray values with respect to time. The inpainting finishes when the gray values reach a stable state.

The proposed scheme employed a variation and implemented the inpainting block with FoE based inpainting and compared it with the scheme when median diffusion inpainting was utilized for compression. The median filtering [6] is a nonlinear order statistic filtering. In this technique, the edges are preserved. Hence it gives a better estimate of I(i,j)ЄΩ where Ω is the region to be inpainted. The parameter H is chosen almost same as the width of inpainting area. This determines the influence of pixel outside to the region to be inpainted. The median separates higher half of the samples to the lower half in a probability distribution function, which satisfies the criteria

$$P(x \leq m) \geq 0.5 \text{ and } P(x \geq m) \geq 0.5,$$

where m is the probability distribution function P(x) median value. In the median inpainting technique, the range is selected by fixing an appropriate value for H.

$$\text{Range}= ((i\text{-}H/2\text{: } i+H/2), (j\text{-}H/2\text{: } j+H/2))$$

The pixel value is then replaced by the median of the selected range.

In the proposed scheme, VQ and SMVQ is incorporated with FoE based inpainting and performance is evaluated. The details of the proposed scheme are discussed in the following section.

2.1. Image Compression and secret data embedding methodology

SMVQ was developed as an improvised version of VQ to alleviate the block artifact of the decompressed image and increase the compression ratio, because the correlation of neighboring blocks is considered and the indices of the sub codebooks are stored.

The compression performance of SMVQ is better than that of VQ. However, the quality of the recovered image may be intolerable as a result of the derailment problem. A simple solution is to use a threshold to control the quality of the decoded image. An indicator is used to express whether the residual block is encoded by VQ or SMVQ. In our scheme, the sender and the receiver both have the same super codebook or the main codebook Ψ with W codeword, and each codeword length is n^2. Denote the original uncompressed image of size M x N as I, and it is subdivided into the non-overlapping n x n blocks. For simplicity in computation, it is assumed that M and N can be divided by n with no remainder. Denote all k divided blocks are scanned successively in a raster scan order as $B_{i,j}$, where $k = M \times N/ n^2$, i = 1, 2,. . ., M/n, and j = 1, 2,. . ., N/n. The blocks in the leftmost and topmost of the image are encoded by VQ directly called seed blocks and are not used to embed secret bits. Codebook generation is the most important and difficult step in VQ process. The codebook is generated by employing LBG algorithm. Of all the VQ codebook generation methods, LBG [8] or the Generalized Lloyd algorithm was found to be the least time consuming and optimal method [15]. In SMVQ, each block can be predicted from its adjacent left and upper block respectively. The bottom row of the upper block will form the upper row of the current block and the rightmost column of the left block will form the leftmost column of the current block except that the topmost left corner pixel is the average of the pixel above and to the left of it respectively. Only these 2n-1 pixels are used to search the main codebook. Mean Squared error (MSE) E^w is calculated between the 2n-1 predicted pixels in the current block with the corresponding values of each transformed codeword of size n^2. The R code words with smallest MSE, i.e., E^w, are aggregated to form a sub codebook for the block. Assume that, among the R code words in sub codebook, the codeword indexed λ has the smallest MSE, i.e., E^r. If the value of E^r is greater than a predetermined threshold TH for distortion control, the current block is encoded by VQ and no watermark bits are embedded. Otherwise it implies it has greater correlation with adjacent blocks. In this scenario, either inpainting or SMVQ is utilized to compress the block according to the secret bit. If VQ is exploited for compression an indicator bit 0 is assigned as a prefix and indicator bit 1 is used if the compression happens by SMVQ or inpainting. In SMVQ, the index value λ occupying $[\log_2 R]$ is used to represent the current block and obviously this will require fewer bits for coding as R < W.

The notion of image inpainting can be traced back to technique used by artists to regain or repair the artworks in an undetectable manner. It has found applications in removal of text, scratches, repairing of damaged photographs, filling in or removal of chosen objects, etc. Digital inpainting came into existence since the previous methods was tedious as it was time consuming. Inpainting algorithms [7] may be of PDE based, convolution based, or which makes use of probabilistic models.

In our scheme, we have employed the FoE based inpainting method [17]. A lot of efforts have been put forward to the development of prior models of generic image structure and such models are extremely vital for many image processing and synthetic tasks. One such example is the Field of Experts (FoE) model which was proposed by Roth and Black. The MRF based model can be applied to arbitrary sized images and is translation invariant. In FoE, a parametric model is used such that it will generalise beyond the training data allowing more extensive computational techniques. While the Products of experts model [18] provides a powerful way of learning distributions on small patches, the results cannot be easily generalised. Making the patch size bigger is intolerable for several reasons. The FoE model addresses the problems of PoE by taking the product over all neighbourhoods. In FoE model the probability density of a full image is expressed as

$$p(x) = \frac{1}{Z(\Theta)} \exp(-E_{FoE(x,\Theta)}) \quad (1)$$

with $E_{FoE(x,\Theta)} = -\sum_k \sum_{i=1}^{N} \log \phi_i (J_i^T x_{(k)}; \alpha_i), \Theta = \theta_1, \theta_2, ...\theta_N$ (2)

where $\theta_i = \{\alpha_i, J_i\}$ and the experts is of the form

$$\phi_i (J_i^T x; \alpha_i) = (1 + \frac{1}{2}(J_i^T x)^2)^{-\alpha_i} . \quad (3)$$

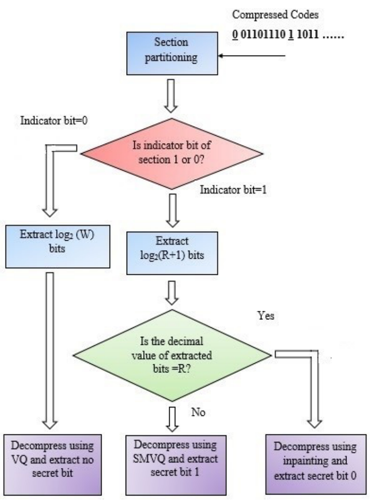


Figure 2. Flowchart of decompression and secret data extraction for each block

Z (Θ) is the partition or the normalizing function. α_i is assumed to be positive. FoE using inpainting simply propagates the information using

$$x^{(t+1)} = x^{(t)} + \eta M\left[\sum_{i=1}^{N} J_i^{-} * \psi_i(J_i * x^{(t)})\right], \quad (4)$$

where η is the user defined learning rate, and t is the iteration index. J_i^- denote the filter obtained by mirroring J_i around its center pixel and $\psi_i(y) = \frac{\partial}{\partial y}\log\psi_i(y_i;\alpha)$ where y is an observed image and x is the true image. The Mask M sets the gradient for all pixels outside of the masked region to be zero.

The index value λ occupying $[\log_2 R]$ bits is used as the shortened code for the block if the secret bit is 0. If its decimal value is equal to R, then secret bit is 1. Each block is assigned either a VQ index code or an SMVQ index code or an image inpainting code. These index concatenated with the indicator bits as prefix forms the compressed codes.

2.2. Image Decompression and secret data extraction methodology

Upon receiving the compressed codes the decoder separates it into indices and secret bits according to the indicator bits. If the present indicator bit is 0, the following $\log_2(W)$ bits will refer to the VQ index. Otherwise, following $\log_2(R+1)$ bits which correspond to λ' are retrieved and its decimal value is computed. If λ' corresponds to R, the residual block was subjected to image inpainting and the watermark bit 0 is recovered. If $\lambda' \in [0,R-1]$, the block corresponding to this chunk was compressed using SMVQ and the embedded watermark bit is 1.

3. Results and Discussion

Several images of size 512x512 were subjected to experimentation to verify the effectiveness of the scheme. The size of non-overlapping blocks was kept as 4x 4. The VQ codebook size and sub codebook size was evaluated with 256 and 15 respectively. The length of each vector was 16 as the block dimension is 4. LBG algorithm was employed during the VQ codebook generation. With the same codebook size, the value of TH greatly determined the hiding capacity. As TH increased, the number of SMVQ blocks and image inpainting blocks increased. As the blocks to be inpainted increased, the median diffusion inpainting could not perform efficiently. From Table 1, it could be inferred that the scheme with FoE inpainting outperformed the scheme with median inpainting both in terms of image quality and computation time. Here the 3x3 FoE model was used. Performance was measured using PSNR, CR and SSIM and computation time. Compression ratio was calculated using the expression

C_R=8 x M x N/L_c, where L_c denote the length of the compressed codes of the image and M and N are the dimensions of the image and M and N are the dimensions of the image.

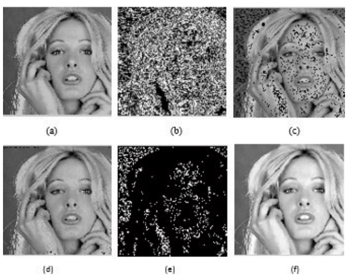


Figure 3. Result when T=80 for Image Tiffany, (a)Original Image (b) Compressed Image (c)Decompressed Image (d) Scheme A (e) Mask (f)Scheme B

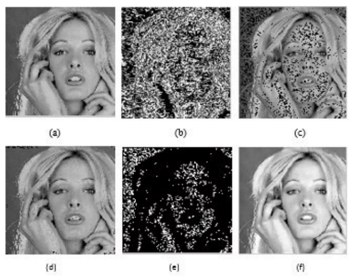


Figure 4. Result when T=100 for Image Tiffany, (a)Original Image (b) Compressed Image (c)Decompressed Image (d) Scheme A (e) Mask (f)Scheme B

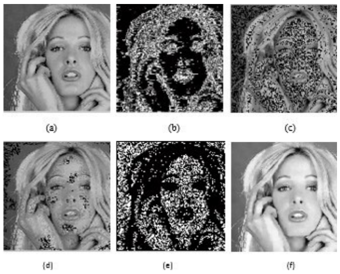


Figure 5. Result when T=300 for Image Tiffany, (a)Original Image (b) Compressed Image (c)Decompressed Image (d) Scheme A (e) Mask (f)Scheme B

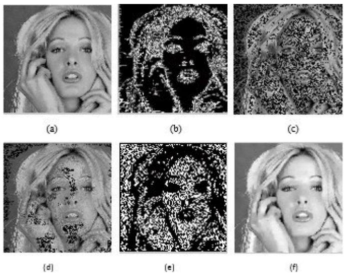


Figure 6. Result when T=500 for Image Tiffany, (a)Original Image (b) Compressed Image (c)Decompressed Image (d) Scheme A (e) Mask (f)Scheme B

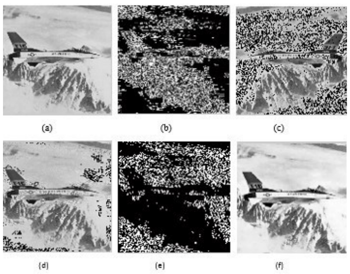


Figure 7. Result when T=80 for Image Airplane, (a)Original Image (b) Compressed Image (c)Decompressed Image (d) Scheme A (e) Mask (f)Scheme B

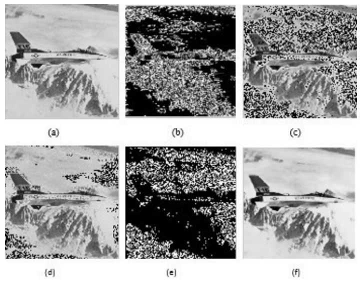


Figure 8. Result when T=100 for Image Airplane, (a)Original Image (b) Compressed Image (c)Decompressed Image (d) Scheme A (e) Mask (f)Scheme B

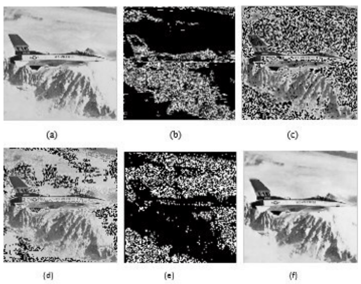


Figure 9. Result when T=300 for Image Airplane, (a)Original Image (b) Compressed Image (c)Decompressed Image (d) Scheme A (e) Mask (f)Scheme B

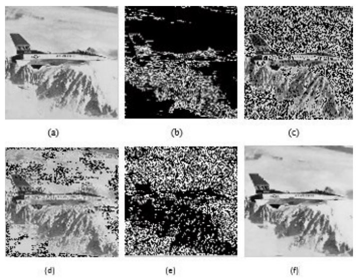
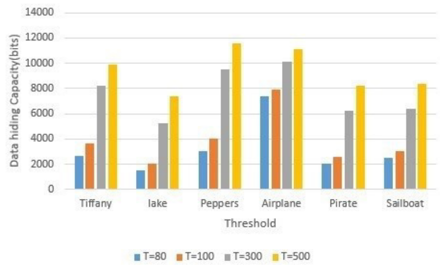


Figure 10. Result when T=500 for Image Airplane, (a)Original Image (b) Compressed Image (c)Decompressed Image (d) Scheme A (e) Mask (f)Scheme B

Table 1. Performance comparison of the proposed scheme with Scheme A (Median inpainting) and Scheme B(FoE based inpainting)

Image	Scheme	T=80				T=100				T=300				T=500			
		CR	PSNR	SSIM	Time (sec)	CR	PSNR	SSIM	Time (sec)	CR	PSNR	SSIM	Time (sec)	CR	PSNR	SSIM	Time (sec)
Lake	Scheme A	14.841	27.755	0.8808	148.213	15.067	25.895	0.8665	204.149	16.693	17.218	0.7285	468.835	17.779	15.380	0.6578	752.223
	Scheme B	14.841	33.541	0.9763	27.935	15.067	33.296	0.9754	28.936	16.693	33.129	0.9651	32.454	17.779	30.542	0.9530	35.564
Tiffany	Scheme A	15.345	27.254	0.8765	399.076	15.787	26.102	0.8611	345.12	18.322	18.309	0.6563	694.283	19.442	16.191	0.5732	1154.318
	Scheme B	15.345	34.822	0.9732	25.994	15.787	34.556	0.9712	26.463	18.322	32.301	0.9508	26.825	19.442	30.905	0.9350	26.923
Peppers	Scheme A	15.523	28.531	0.8986	288.654	15.983	27.224	0.8852	369.797	19.184	18.063	0.6952	784.71	20.771	15.966	0.5729	911.48
	Scheme B	15.523	35.789	0.9787	26.219	15.983	35.565	0.9772	26.385	19.184	33.301	0.9608	27.092	20.771	32.760	0.9455	27.379
Airplane	Scheme A	17.802	15.123	0.7494	588.560	18.13	13.905	0.7011	641.339	19.612	11.762	0.5283	782.216	20.395	11.751	0.4944	889.556
	Scheme B	17.802	34.045	0.9739	29.180	18.13	33.635	0.9731	30.453	19.612	31.909	0.9611	30.208	20.395	31.553	0.9547	35.429
Pirate	Scheme A	15.069	28.682	0.8896	205.635	15.292	28.335	0.8816	251.861	17.148	22.442	0.7798	550.320	18.313	19.314	0.7021	1586.684
	Scheme B	15.069	34.190	0.9692	54.324	15.292	33.978	0.9669	54.883	17.148	31.988	0.9459	57.362	18.313	30.516	0.9270	63.317
Sailboat	Scheme A	15.267	27.031	0.8907	233.031	15.517	25.838	0.8799	281.327	17.236	20.318	0.7893	551.648	18.441	18.106	0.7127	701.166
	Scheme B	15.267	33.887	0.9705	32.954	15.517	33.742	0.9691	33.725	17.236	32.178	0.9516	34.653	18.441	30.676	0.9341	37.954

Figure 11. Relationship between data hiding capacity and thresholds with codebook size 256



4. Conclusion

In this project, an integrated data hiding and compression scheme was implemented to increase the efficiency in communication. The topmost and leftmost blocks were compressed by VQ and the remaining blocks were compressed either by SMVQ or image inpainting method when the Mean Square Error was less than the threshold. VQ was employed to control the distortion on a threshold basis when the mean square error was greater. The watermark bits decided whether the SMVQ or inpainting method to be used for compression. Together with VQ and SMVQ, image inpainting could take upon the role of compression and data hiding capacity was improved. At the receiver side the compressed codes were partitioned to watermark bits and indices to get the decompressed image. An interesting point to note is that it can be used for covert communication. The receiver can decode and extract the secret bits by observing the compressed codes provided it has the state codebook size as well as the main codebook size without undergoing the image reconstruction procedure. The experimental results show that the proposed scheme with FoE based inpainting outperformed the scheme with median diffusion inpainting.

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